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Hydrology and Earth System Sciences, 8(1), *23–34* (2004) © EGU

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Abstract

Although it is well known that forest canopies reduce the amount and intensity of precipitation at the ground surface, little is known about how canopy interception modifies extreme events. This research investigated the effects of forest cover on intensity-duration-frequency relationships using a stochastic model to extrapolate measured rainfall and throughfall to throughfall expected during extreme events. The model coupled a stochastic model of rainfall with stochastic representations of evaporation and precipitation transfer through canopies. Stochastic evaporation was governed by probability distributions sensitive to storm size, and transfer through canopies was governed by a black-box linear system. The modelled reduction of extreme-event intensities by canopies was 5–30%, depending on duration and return interval. The reduction was 15–20% in low return interval events (2 y) at all durations. In contrast, intensities of high return interval events (90 y) were proportionally more reduced at short durations (~30% reduced) than at long durations (~5% reduced). The model suggested that evaporative losses reduced intensity in the frequent events (2 y return interval), but water transfer through the canopy was more important for the reduction in intensity in the rarest extreme events. High return intervals of long duration were least affected by canopies because evaporative losses were the least proportion of rainfall. Extreme events larger than 10- or 20-y return interval probability threshold occurred only 31–69% as often in throughfall as in rainfall.

Keywords: canopy interception, throughfall, stochastic rainfall modelling, rainfall intensity, linear systems, landslides

Introduction

Forest canopies modify precipitation so that throughfall differs in amount and intensity from rain falling on forests. Of the processes involved in canopy interception, the best-described is evaporation, where work has included process-level investigations at small spatial and temporal scales (e.g. Rutter *et al.*, 1971; Murphy and Knoerr, 1975; Gash *et al.*, 1999; Klaassen, 2001) and development of models useful at larger spatial and temporal scales (e.g. Sellers *et al.*, 1996; Ramírez and Senarath, 2000). In contrast, published observations of canopy effects on intensity are rare. Trimble and Weitzman (1954) were the first to report the effect of canopies on intensity, but little progress has been made since to quantify how vegetation affects precipitation rates. Several studies have shown lagging and damping of rainfall intensities under canopies (e.g. Rutter *et al.*, 1971; Massman, 1983; Schellekens *et al.*, 1999; Xiao *et al.*, 2000b; Keim and Skaugset, 2003), but most canopy interception research has been to estimate time-integrated quantities. Keim (2003) developed a black-box approach to predict throughfall intensities at high temporal resolution during rainfall, but there have been no investigations of this process at longer timescales that encompass extreme events. As a result, little is known about the overall effects of canopy interception on catchment hydrology aside from simple water budgets.

A promising approach to understand the effects of canopy interception on evaporation and intensity smoothing over long time scales is stochastic modelling. Stochastic models supplement existing data to clarify interactions between soil, vegetation and atmosphere that affect the water cycle. Predicting effects of human activities on these interactions is facilitated by a stochastic approach that can account for temporal variability as well as deterministic relationships. Precipitation is one hydrological variable that is well suited to stochastic representation, and an extensive literature documents progress in developing these models (see Wilks and Wilby, 1999, for a partial review). Combining stochastic precipitation models with process-based hydrological models can produce powerful tools for application in a variety of unmeasured situations, such as efforts to predict streamflow (e.g. Kurothe *et al.*, 1997; Cameron *et al*., 1999; Burlando and Rosso, 2002), soil erosion (e.g. Tiscareno-Lopez *et al.*, 1993; Baffaut *et al*., 1998), landsliding (Benda and Dunne, 1997a), sediment transport (Benda and Dunne, 1997b), and catchment geomorphology (Tucker and Bras, 1998).

Identifying appropriate model structure and values of parameters for stochastic models of rainfall requires data that contain all the variability that the stochastic simulations are expected to reproduce. This requires long-term records (20 years or longer) of rainfall from meteorological stations. Unfortunately, similar data of throughfall to parameterise a stochastic model of throughfall are lacking, mainly because most throughfall data were collected for specific research over short periods of time by varying methods.

The goal of this research is to use existing data of rainfall and throughfall to estimate the effects of forest cover on intensity-duration-frequency relationships of rainfall and extreme events. In this paper, a new stochastic model of temporal throughfall is presented that uses stochastic representations of canopy evaporation and intensity smoothing to modify an existing stochastic model of rainfall, without requiring long records of throughfall. Parameters describing the stochastic interception effects can be estimated from relatively short (i.e. 1 or 2 seasons) records of rainfall and throughfall by estimating evaporation and intensity smoothing effects of canopies separately.

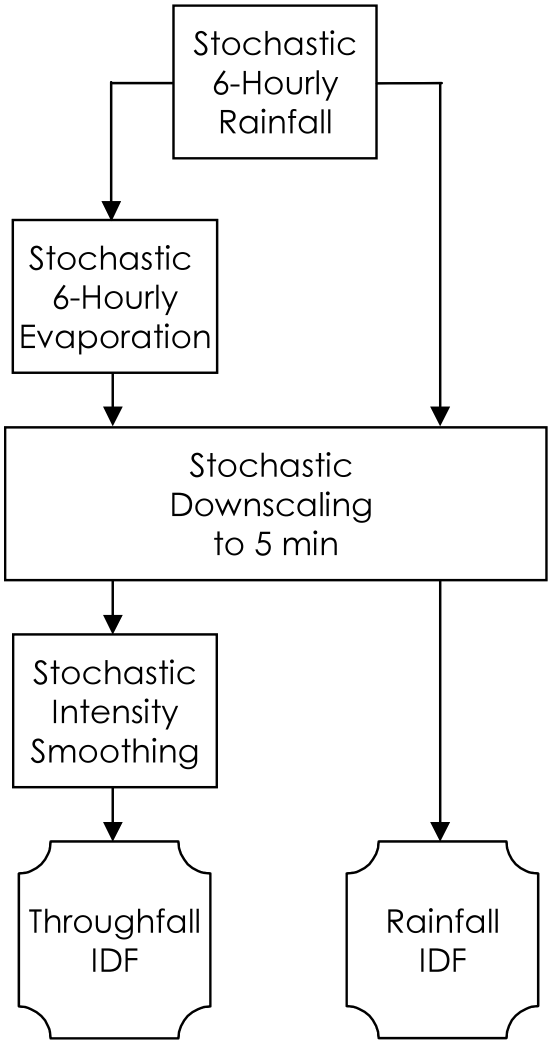

Fig. 1. *Schematic of a stochastic model of temporal throughfall.*

Methods

MODEL OVERVIEW

The stochastic model of throughfall consists of a stochastic model of rainfall modified by stochastic evaporative loss for every storm and stochastic smoothing of intensity within each storm (Fig. 1). Evaporation from canopy interception is represented by stochastic evaporation loss at a 6-hour timescale and stochastic intensity smoothing is represented by a linear convolution operating at a 5-minute timescale. The 6-hour time step for simulating evaporation matches the length of a storm (mean storm lengths from the data used were 4–18 h, depending on the site). The 5-minute timescale for intensity smoothing is near the limit of resolution of the tipping-bucket rain gauge data used to parameterise the model. It was selected as a compromise between the desire to simulate processes at short timescales and to reduce effects of errors in the data.

To achieve the objectives of understanding the effects of vegetation on statistical properties of throughfall, the number of variables was kept small and the model structure simple. The greatest simplifications are in simulation of evaporation. Specifically, the model simulates evaporation at a 6-hour timestep by subtraction of evaporated mass, evenly distributed over each 6-hour time period. The model does not simulate serial correlation of evaporation at any time scale or variance of evaporation at shorter time scales. Therefore, realisations of the model may not be suitable as boundary conditions for other physically-based models of catchment hydrology or soil-vegetation-atmosphere transfer of water. The model does, however, respect the long-term distribution of storm-scale evaporation. This allows estimation of throughfall statistics, especially those pertaining to extreme events.

RAINFALL

The stochastic representation of throughfall does not depend strictly on the structure of the rainfall model. However, simulating the intensity-smoothing phenomena in throughfall at short timesteps requires a stochastic model of rainfall that simulates rainfall intensities at the same short timestep. This work used a rainfall model by Rupp *et al.*, (2000) which is structured as a multiplicative random cascade. In short, a multiplicative random cascade begins with the total rainfall mass over the period to be simulated, then disaggregates mass to lower (higher-resolution) timescales by assigning mass stochastically to successively subdivided time periods (Schertzer and Lovejoy, 1987; Gupta and Waymire, 1993). The proportioning of mass from one timescale into time periods at the next lower timescale is governed by probabilities determined by mass of rainfall and timescale (similar to the models of Olsson, 1998 and Menabde and Sivapalan, 2000). The advantages of the random cascade structure include proper representation of the temporal scaling of rainfall and good reproduction of variance at long timescales (both important for simulating, for example, intensity-duration-frequency curves), as well as the explicit simultaneous simulation of rainfall at several nested timescales.

The rainfall model was calibrated using data from several sources in western Oregon, USA. The long-timescale data were observations of daily rainfall (1889–1999) from Corvallis, Oregon (75 m msl). The medium-timescale data were observations of hourly rainfall (1984–1999) from Corvallis. The short timescale data and mean annual precipitation of 2260 mm were from a tipping-bucket rain gauge (1988-2000) near Johnson Creek (250 m msl) in the central Oregon Coast Range, 20 km northeast of Reedsport, Oregon. The climate of this area is strongly seasonal, with 80% of precipitation occurring in frontal storms during October to March, and only 5% occurring during the summer months. Snowfall and convective rainstorms are negligible. Extreme precipitation events normally occur during autumn and winter, when subtropical frontal storms are enhanced by orographic uplift.

EVAPORATION

The proportion of precipitation that is intercepted and evaporated is a complicated function of many meteorological and vegetative conditions (e.g. Murphy and Knoerr, 1975; Gash *et al.*, 1999; Klaassen, 2001). Deterministic approaches to modelling evaporation by these processes have dominated the canopy interception literature (e.g. Rutter *et al.*, 1971; Gash, 1979; Xiao *et al.*, 2000a), and these models could serve as a way to use stochastic weather data to predict evaporation. The objectives of this research are only to estimate vegetation effects on precipitation in the statistical sense. Therefore, it was decided to simplify the model structure and model the evaporation solely as a stochastic function of precipitation amount.

The evaporation data available were summarised by storm total. For estimating evaporation at the 6-hour time scale, the probability distribution of proportional evaporative losses in 6-hour time steps was assumed to be the same as that of the storm-total proportional evaporative losses for any given precipitation amount. Thus, observations of storm-total precipitation and throughfall were used to parameterise evaporation loss probabilities.

Rainfall – throughfall data

Rainfall and throughfall data were asembled from five forests where the dominant species was Douglas-fir (*Pseudotsuga menziesii*). Two of these sites were in the McDonald/Dunn Research Forests of Oregon State University near Corvallis, Oregon, USA. The site in the McDonald Forest was a young natural stand with 48-year old trees that averaged 37 m tall. Throughfall was collected in ten 157-mm-diameter rain gauges (Krygier, 1971). The site in the Dunn Forest was a thinned, natural stand with trees 60 years old that averaged 32 m tall. Throughfall was collected in three troughs, 19 mm × 4 m, each routed to tipping-bucket rain gauges (Keim and Skaugset, 2003). Two sites were in the Gifford Pinchot National Forest of south-western Washington State, USA. One Washington site was Cedar Flats Research Natural Area near Mt. St. Helens, where the oldest trees were 600 years old and up to 84 m tall. Throughfall was collected in seven trough collectors identical to those used in the Dunn forest (Keim and Skaugset, 2003). The other Washington site was at the Wind River Canopy Crane, near Carson, Washington, where the oldest trees were 500 years old and up to 60 m tall. Throughfall was collected in 24 roving 10-cm-diameter tipping-bucket gauges (Link *et al.*, in press). The final site was a plantation in the Malalcahuello Forest Reserve, IXth Region, Chile, where the trees were 27 years old and 25 m tall. Throughfall was collected in one gutter, 10.5 cm × 24 m, routed to a storage tank (Iroumé and Huber, 2002; with additional original data for this research).

Climates at the five sites all exhibit seasonal precipitation patterns, dominated by marine frontal storms with precipitation enhanced by orographic effects. Snow is most common at the sites in Washington, but these data were removed from the analysis. Overall, these five sites encompass a range of age and canopy structure of Douglas-fir stands, providing this study with a broad inferential base across the range of this species.

Data for this project were of varying temporal and spatial resolution. The coarsest temporal resolution was in the data from the McDonald Forest, where storm-total measurements were made at depth resolution of 0.254 mm. There was no effort to verify that the 10 gauges used were sufficient to estimate the mean throughfall in this stand. Data from the Dunn forest and Cedar Flats were collected by event-recording dataloggers connected to tipping buckets at a resolution of 0.127 mm. Geostatistical analyses of the spatial variability of throughfall indicated that the lengths of the collecting troughs were similar to the minimum lag at which pairs of storm-total observations of throughfall were least correlated in both stands (Keim, 2003). Data from the Wind River Canopy Crane were collected by event-recording dataloggers connected to tipping buckets at a resolution of 0.254 mm. Comparison with 44 storage gauges, measured and relocated manually after varying lengths of time at this site, indicated 2.1% study-wide difference between the two types of gauges and suggested that the tipping bucket data were accurate estimates of the mean throughfall (Link *et al.*, in press). A recording float in the throughfall storage tank at the Chilean site recorded throughfall in intervals of 0.24 mm. The trough at that site was ten times larger than the minimum catch area required to estimate the mean of throughfall in that stand (A. Huber, personal communication).

Stochastic representation

Two features of the relationship between storm-total precipitation and storm-total throughfall (precipitation – evaporation) in these forest stands combine to permit simple stochastic representation. First, the relationship was similar among the five sites (Fig. 2). Differences in study methods, forest age, canopy structure and tree size suggest that evaporation data might differ systematically among stands, but climatic and storm-to-storm variability overwhelmed these differences sufficiently for all stands to be treated alike. Second, fractional throughfall has the lowest mean, highest variance and highest skew for small storms, but highest mean, lowest variance and lowest skew for large storms (Fig. 2).

This was modelled by treating throughfall, T_p (%), as a random variable associated with the independent variable storm-total rainfall, R (mm), and represented by a gamma

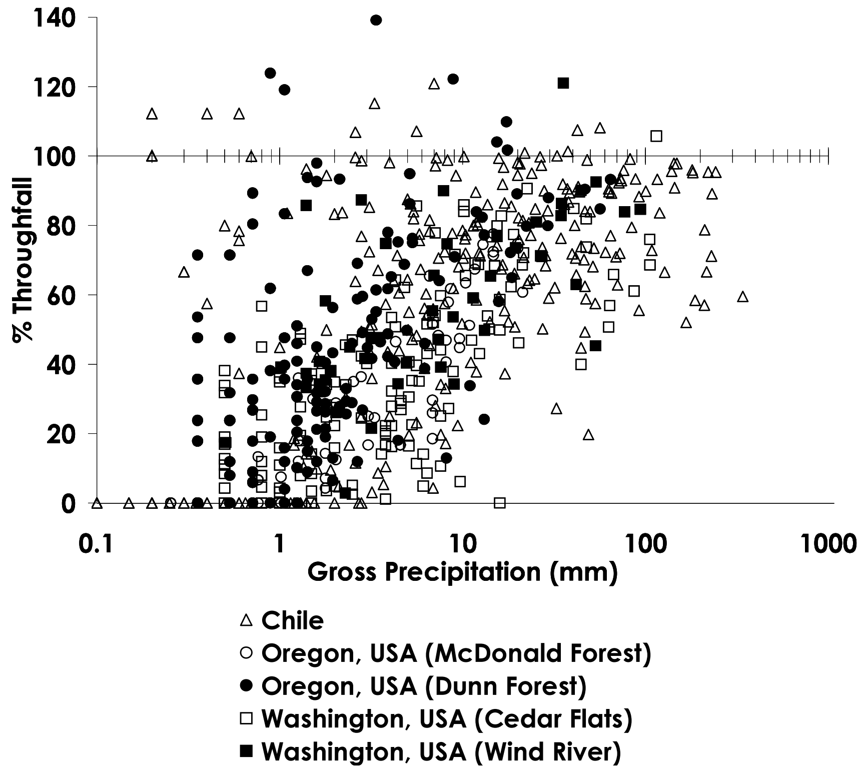

Fig. 2. *Relationship between total storm precipitation and percent throughfall in five different Douglas-fir forests in Chile and the northwestern USA.*

probability density function (PDF) with parameters that varied by storm-total precipitation. The possible values of T_p modelled this way range from zero to infinity. This allows for $T_p > 100$, which indicates that evaporation is less than occult precipitation (impaction of cloud droplets or condensation on canopy surfaces), but disallows negative T_p that indicates more evaporation than rainfall. There were data for several storms where $T_p > 100$ (Fig. 2), and $T_p < 0$ is impossible.

The gamma distribution is given by

$$T_p = \frac{R^{\alpha-1}e^{\left(\frac{-R}{\theta}\right)}}{\Gamma(\alpha)\theta^{\alpha}} \; , \quad (1)$$

where T_p is the percent throughfall occurring in any given storm or 6-hour period, R is the total precipitation in that same period, α and θ are parameters, and Γ is the gamma function. Values of α and θ were estimated for 18 ranges of R; the limits of each range were defined to include at least 30 observations and the ranges were allowed to overlap by 50%. L-moments (Hosking, 1990) were used to find the best-fit sets of α and θ for PDFs of T_p in each range of R (Fig. 3); then these parameter sets were aassociated with the midpoint of the range and curves to α and θ were fitted as functions of R (Fig. 4).

The best fits for the R-α and R-θ curves (Fig. 4) were found by minimising the sum of squared differences between the moments predicted by candidate R-α and R-θ curves and the observed moments of T_p (Fig. 5). Inability to identify α in storms larger than 10 mm (Fig. 4) led to reduction in the parameterisation of the model by one by defining $\alpha = 1/\theta \times f(R)$, with $f(R)$ defined to fit predicted T_p to the observed means (Fig. 5). In essence, this procedure fitted θ to the mean R-TF curve by varying $\alpha\theta$, which is the first moment of the gamma distribution (mean T_p at each rainfall intensity). Parameter fits were obtained only after setting the asymptotic expected mean $T_p = 82$ for large storms (Figs. 2, 4). This value was chosen as the expected mean T_p for the largest storms on the assumption that the largest storms would have the least evaporative loss, yet not much more than the largest storms observed. In a rainfall-throughfall relationship familiar in canopy interception work (e.g. Leyton, 1967), this asymptote corresponds to the slope of the linear regression of T (mm) on R (mm) for large storms. Values of this asymptote in the literature range from about 0.6 to 1.0, depending on vegetation and climate, which corresponds to 0 to 40% evaporative loss from the largest storms.

The result of varying parameters of the gamma distribution smoothly through rainfall space is an R-dependent PDF. In this way, percent throughfall is represented stochastically,

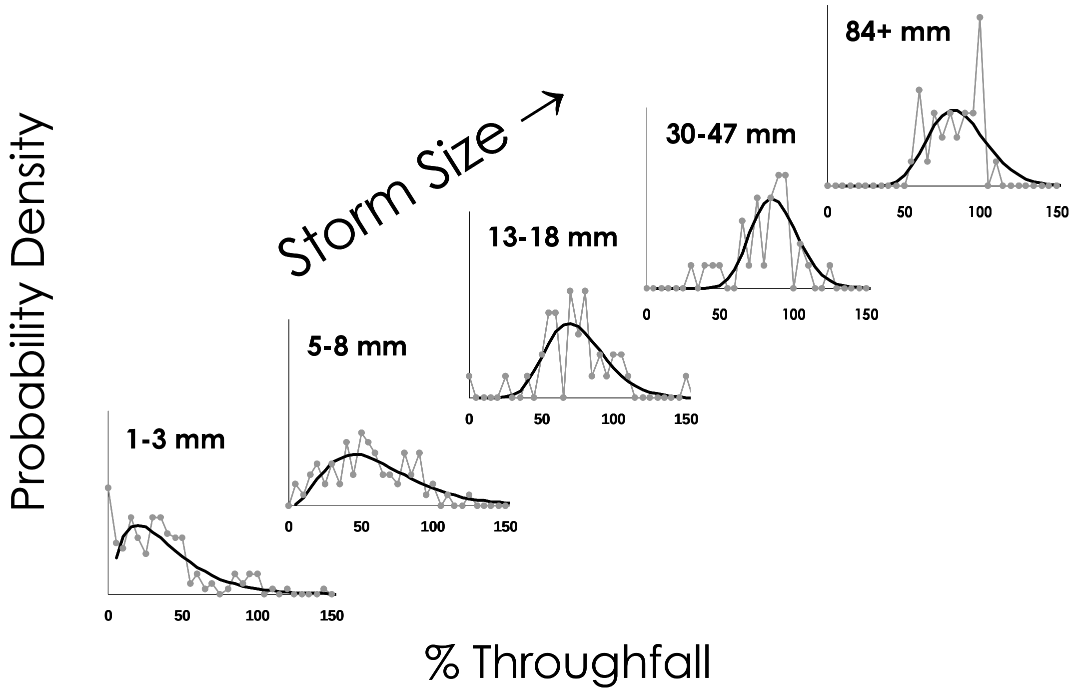

Fig. 3. *Probability density of percent throughfall as a function of storm size for rainfall-throughfall data lumped across five sites in Chile and the northwestern USA. Each subplot shows a histogram of observed percent throughfall for a range of total rainfalls (gray line), and a fitted gamma distribution (black line). Only five sample ranges of total throughfall are shown; the completed analysis contained 18 overlapping ranges. Throughfall for some storms in excess of 100% indicates occult precipitation > evaporation.*

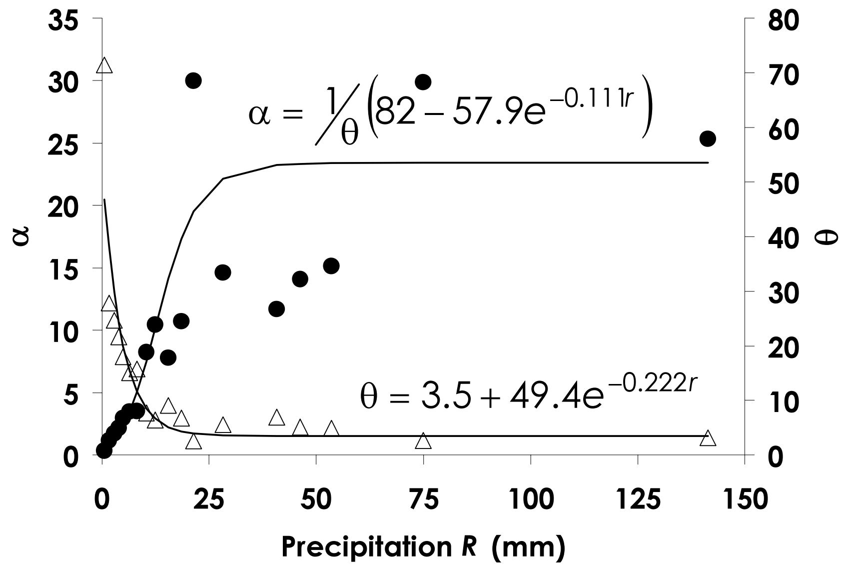

Fig. 4. *Best-fit parameters of a gamma distribution fitted to percent throughfall for each of 16 ranges of total precipitation (dots), and fitted functions of parameters determined by total precipitation (solid lines and equations). Data are lumped from five sites in Chile and northwestern USA.*

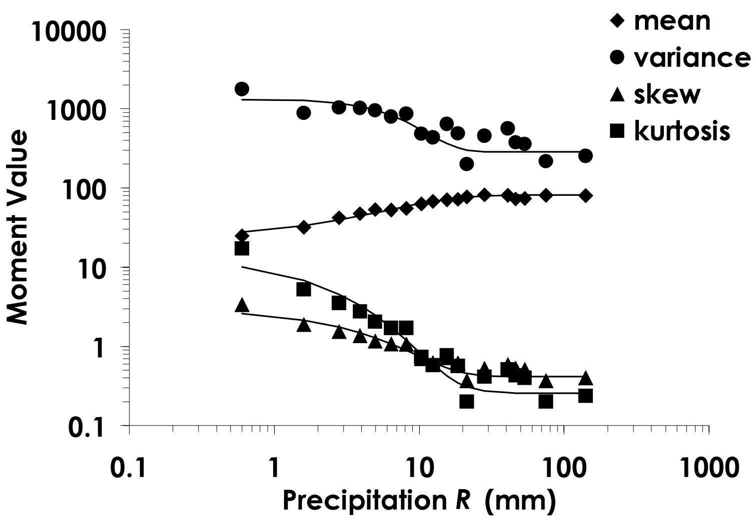

Fig. 5. *First four moments of percent throughfall for each of 16 ranges of total precipitation (dots at median of each range), and moments modelled using a gamma distribution with precipitation-dependent parameters (solid lines). Data are lumped from five sites in Chile and northwestern USA.*

with just one independent fitted parameter (θ) and one physically-based parameter (asymptotic T_p).

INTENSITY SMOOTHING

After removing the stochastic evaporation from the random cascade model of rainfall at the 6-hour timescale (2^{-2} days), the cascading downscaling of precipitation to the 5.625-minute timescale (2^{-8} days) was resumed for subsequent simulation of intensity-smoothing effects of vegetation (Fig. 1).

Intensity smoothing was modelled following Keim (2003). He used a linear system convolution to model a time series of throughfall from a time series of rainfall and mimic damping and lagging rainfall intensity by the canopy. This method treats the canopy as a catchment using the familiar unit hydrograph approach to flow modelling (Dooge, 1959, 1973). The model predicts throughfall rate, $T(t)$ (mm h^{-1}), from rainfall rate, $R(t)$ (mm h^{-1}):

$$T(t) = \int_0^t R(t)g(t-\tau)d\tau \quad , \tag{2}$$

where τ is a shift in time, and $g(t-\tau)$ is a transfer function defining the response of $T(t)$ at time shifts τ after $R(t)$. Conceptually, Eqn. (2) describes how the signal $R(t)$ is filtered by $g(t-\tau)$ to produce an output signal $T(t)$. Following the approach of Keim (2003), the system was defined with a single input of precipitation corrected for evaporation (i.e. all precipitation that will eventually reach the ground), using the 5.625-min-resolution (2^{-8} d) stochastic simulations for $R(t)$ corrected for evaporation.

In practice, $g(t-\tau)$ is not known *a priori*, and must be inferred from $T(t)$ and $R(t)$. Keim (2003), using the summation form of Eqn. (2), estimated the form of $g(t-\tau)$ for 48 rainstorms from the Dunn Forest and Cedar Flats sites by optimising parameters in trial forms of g to maximise model efficiency (Nash and Sutcliffe, 1970) to predict measured throughfall in response to rainfall. Three findings of Keim (2003) were useful for this modelling: (1) simple, one-parameter models of $g(t-\tau)$ were adequate to simulate $T(t)$ with high model efficiency (see Fig. 6 as an example); (2) values of parameters were statistically independent of measured storm characteristics; and (3) transfer function parameters were not significantly different between the two stands. Intuition suggests that transfer times through canopies should vary among sites but, as was the case with evaporation, variability among events was greater than differences among sites, so the canopies were lumped for model parameterisation.

Taking advantage of these characteristics, the exponential distribution was selected as a simple, one-parameter transfer function to govern intensity transformations by canopies. The exponential distribution is given by:

$$g(t) = ae^{-at} \quad , \tag{3}$$

where a is a parameter. Some form of exponential drainage from canopy storage is a common assumption. Although data from laboratory tests have shown that this simplest form Eqn. (3) does not describe canopy storage as well as related forms with additional parameters (e.g. Calder, 1977; Keim, 2003), it performs nearly as well as higher-parameter models in the face of variable field conditions (Keim, 2003).

The values of a over all 48 storms at all throughfall collectors in the Dunn Forest and Cedar Flats site (Keim, 2003) appeared to be log-normally distributed (Fig. 7). To simulate intensity smoothing in the model, a was generated randomly from this distribution to parameterise Eqn. (3), then, using Eqn. 2, the evaporation-corrected 5.625-minute simulation of rainfall was convolved with Eqn. (3) to generate the final simulation of stochastic throughfall. The median value of a was 0.10, which corresponds to a mean residence time of precipitation in the canopy of 10 minutes.

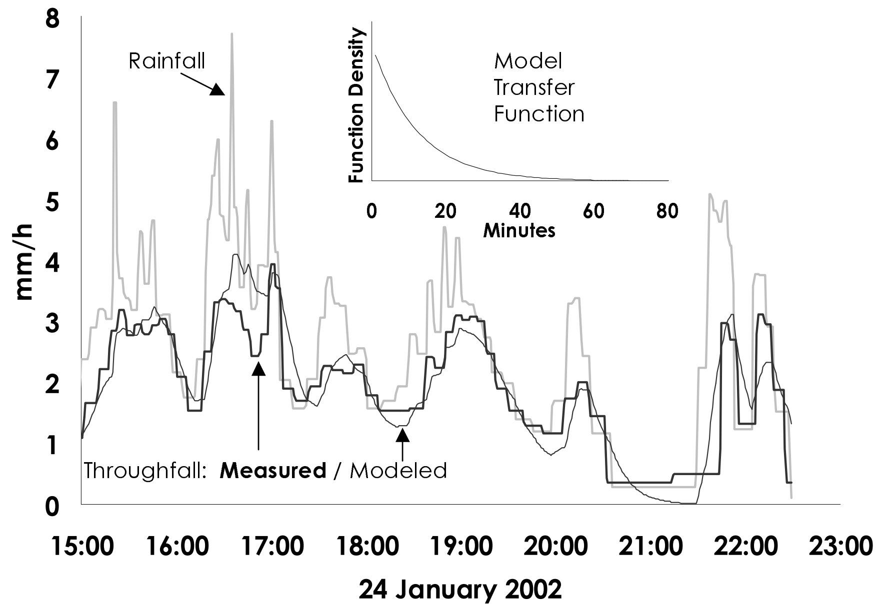

Fig. 6. *Example of throughfall predicted (thin black line) from rainfall (gray line) using a simple linear system governed by an exponential transfer function (inset) and optimised to reproduce observed throughfall (thick black line). Data are from the Dunn Forest site in western Oregon, USA.*

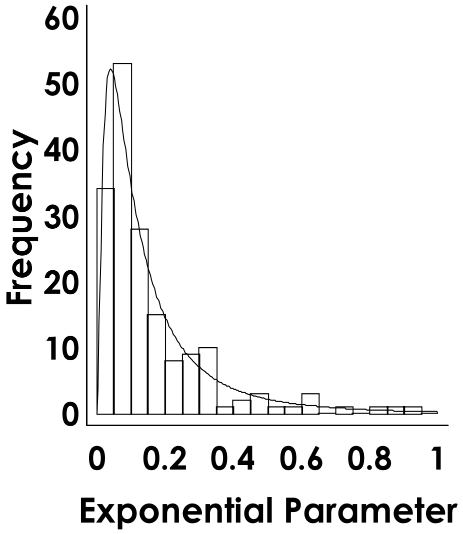

Fig. 7. *Histogram of best-fit parameters for an exponential distribution transfer function in a linear system for predicting throughfall rates from rainfall rates at the Dunn Forest and Cedar Flats study sites, northwestern USA. The solid line indicates the best fit of the lognormal distribution to the data.*

Results and Discussion

EVAPORATION

Over a 179-year simulation, the stochastic model of throughfall predicted interception loss of 24% of gross precipitation (T_p = 76), matching the lumped data. Thus, the representation of interception evaporation that was dependent on rainfall and generated by a gamma distribution was able to reproduce long-term observed mean evaporation rates. However, modelled variance of T_p was about 20% higher than that observed for storms larger than 60 mm (Fig. 5; note the log-scale axes), leading to poorer simulation of evaporation in the largest storms, specifically in the events with T_p > 100 (Fig. 8). Parameterising the gamma distribution to remedy these problems is possible, but choosing an objective way to do this would be difficult given sparse data.

INTENSITY-DURATION-FREQUENCY: EXTREME EVENTS

Comparing intensity-duration-frequency (IDF) curves of throughfall simulations with rainfall simulations (Fig. 9) showed a general reduction in extreme precipitation events by the canopy (Fig. 10). This reduction in intensity averaged 15–20% for all durations and return periods; however, the reduction varied with event frequency and duration. Low return period events showed a constant intensity reduction by the canopy across the full range of durations (solid gray line, Fig. 10). Rainfall intensities of large, high return period events were reduced more at short durations and less at long durations than were small, low return period events (solid black line, Fig. 10).

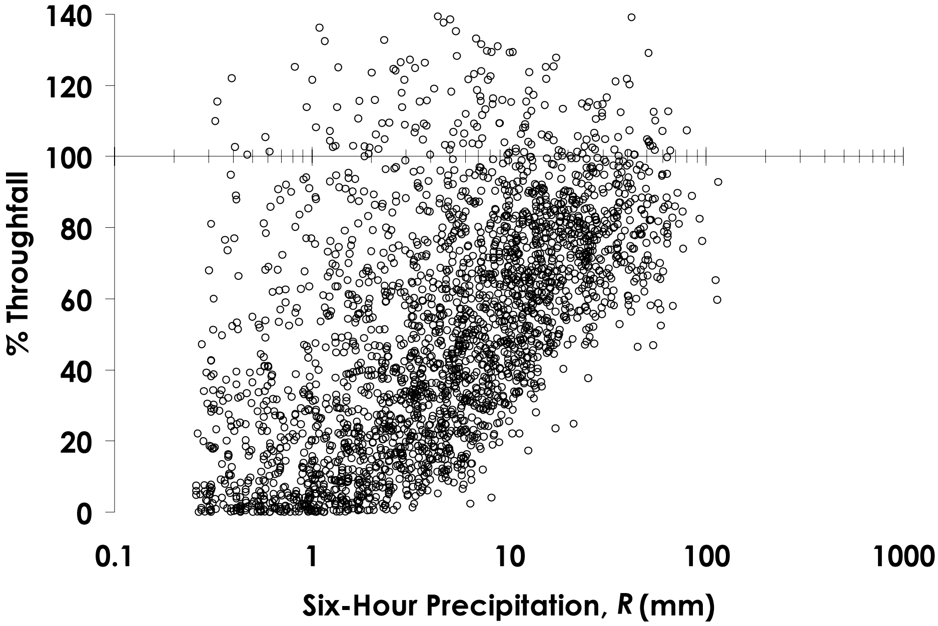

Fig. 8. *Example stochastic simulation of 8 years of throughfall as a percentage of simulated rainfall. Each dot represents a six-hour period, which is defined as the length of a storm. Compare to data in Fig. 6.*

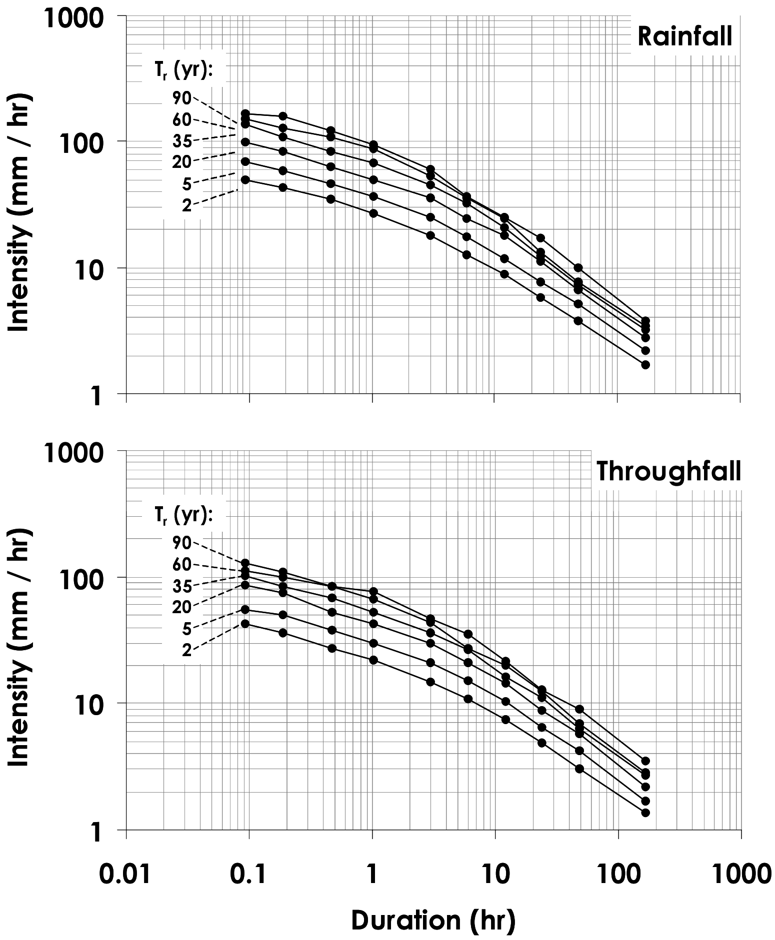

Fig. 9. *Intensity-duration-frequency relationships for a 179-year stochastic simulation of rainfall and throughfall. Each dot is a simulated (not fitted) value plotted at the Weibull plotting position for a series of annual maximum intensities. T_r is the return period.*

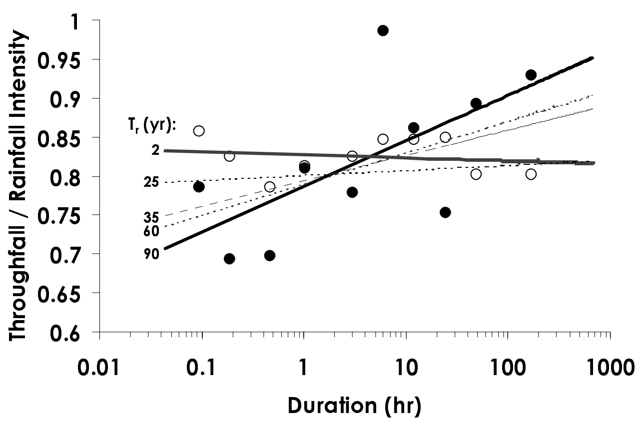

Fig. 10. *Attenuation of simulated extreme events by forest canopy in a stochastic model of throughfall. Open circles are ratios of throughfall intensities to rainfall intensities calculated for a 2-year-return-period (T_r) event (gray line is the log-linear regression relationship), and filled circles are for a 90-year event (black line is the regression relationship). Dashed lines indicate regression relationships for three other return periods.*

At long durations, the largest events are less attenuated by forest canopy than the smaller, more frequent events because mean T_p increases with R, and there is least total interception loss in the largest long-duration storms. The canopy effect of intensity smoothing does not affect IDF curves in the long duration storms because the smoothing occurs at shorter timescales.

The attenuation of intensities by the canopy at the shortest durations (< 1 h) includes effects of both evaporative loss and intensity smoothing. The high return period intensities are most affected by the intensity smoothing effect because of the assumptions of the convolution model. Specifically, rainfall during periods of high intensity is smoothed proportionally regardless of the magnitude of input, but antecedent throughfall rates are on average a smaller proportion of rainfall during the very highest intensities. The resulting aggregate intensity is therefore a smaller proportion of high intensity rain than low intensity rain. It is also possible for some throughfall events not to be contemporaneous with the corresponding (i.e. in the same year) rainfall events. This could occur if, for example, occult precipitation exceeds evaporative loss producing $T_p > 100$ in the maximum annual throughfall event, while the maximum annual rainfall event occurred at some other time. However, this is not likely to be the source of the most extreme throughfall events.

Another way to quantify the difference between IDF curves of rainfall and throughfall is by the difference in return period of events of a given magnitude. This type of analysis allows the frequency of events above thresholds of interest to be estimated. For example, threshold values of precipitation intensity and duration have proven useful for identifying events that are sufficient to cause widespread landsliding (e.g. Caine, 1980; Keefer *et al*., 1987; Larsen and Simon, 1993; Terlien, 1998) without requiring identification of the physical causes of individual slides. The 10-y and 20-y return intervals were selected as example intensity-duration thresholds.

Modelled events large enough to reach these thresholds occurred less frequently in throughfall than in rainfall (Fig. 11) because of simulated evaporation and intensity smoothing by canopy interception. Return intervals for throughfall events equivalent to 10-y precipitation events ranged from 15 to 32 years, depending on duration. Similarly, return intervals for throughfall events equivalent to 20-y precipitation events ranged from 29 to 52 years, depending on duration. If the example thresholds correspond to, say, landslide-producing events, these results suggest that hillslopes under forest canopies are likely to experience destabilising hydrological conditions with only 31 to 69% of the frequency experienced by hillslopes in openings.

The lack of sufficient data makes it impossible to verify or refute the predictions of the model in relation to intensity smoothing and IDF curves. The results of the model suggest that canopies are most effective in attenuating the most extreme intensities, but it is important to remember that there are only limited observations of this phenomenon (e.g. Keim and Skaugset, 2003) and the predictions in the field have not been fully tested. Many more rainfall and throughfall observations during intense rainfall and at high temporal resolution would be needed for direct testing of the predictions presented in this paper. The strategy of estimating effects of canopies on extreme events by extrapolating from data of those effects in smaller events follows the paradigm suggested by Hall and Anderson (2002). These methods, uncommon in hydrology, may be the only way to make predictions about events that are not normally measurable.

There are many sources of uncertainty in the 179-year simulation of rainfall and throughfall presented here. These include errors in measuring rainfall and throughfall and errors arising from small sample sizes in estimating probability distributions governing both the rainfall and throughfall models. Assessing the effects of these uncertainties on predictions of the model using established methods such as GLUE (Beven and Binley, 1992) is prevented by the lack of data suitable for model validation.

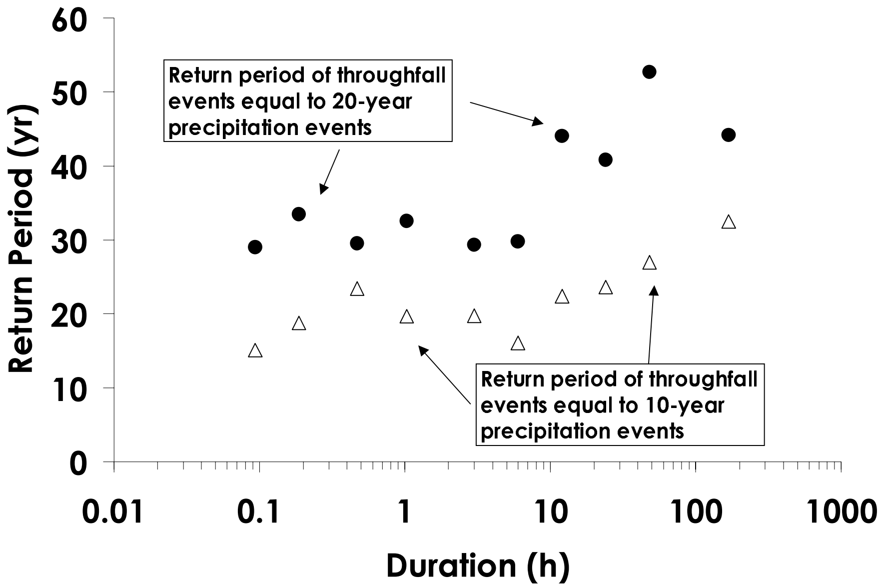

Fig. 11. *Simulated effect of canopy interception evaporation and intensity smoothing on the frequency of extreme precipitation events over example thresholds of 10- or 20-year return period. Symbols indicate the return interval of throughfall events equal to precipitation events of 10 y (open triangles) and 20 y (filled circles) return intervals for several durations.*

Generally speaking, uncertainty increases with return period for two reasons. First, uncertainty is greatest in the extreme tail of probability distributions of rainfall. Second, the model of evaporation and intensity smoothing depends mainly on data from mundane events. Formal analysis of uncertainty awaits development of methods appropriate to models of extreme events (Hall and Anderson, 2002) and users of the model presented in this paper should exercise caution in applying the results.

Conclusions

This research has demonstrated that stochastic representations of canopy transformation of precipitation by evaporation and intensity smoothing can be coupled with a stochastic model of rainfall to produce a stochastic model of throughfall. By explicitly modelling the evaporation and intensity-smoothing effects separately, the model can be parameterised using relatively short sets of data. This allows the model to be used to estimate the probabilistic effects of forest canopies on extreme precipitation events without requiring long records of throughfall.

Comparing the predicted intensity-duration-frequency (IDF) relationships for rainfall and throughfall in the context of landslide initiation suggests the importance of vegetative cover in controlling hydrological processes. When parameterised with data from five forests in Chile and the USA, the model predicts reductions in extreme events by up to 30% in magnitude or about 50% in frequency. Parameterising the model for other climates and vegetation would result in different estimates of vegetative effects on extreme events.

As far as the authors know, these are the first published IDF curves for throughfall. Because no data exist to allow direct construction of these curves, the model results can be only untested estimates. It is unlikely that data will ever exist to test these predictions directly, so indirect tests must suffice. More work would be required to develop such tests, which might consist of a combination of innovative field measurements and models.

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